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Short-term Load Forecasting of an Interconnected Grid by using Neural Network

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Abstract: - With the rapid growth of power system and the increase in their complexity of the networks, load forecasting plays a vital role in economic operation of power systems, network planning and infrastructure development. Electricity demand forecasting is concerned with the prediction of a very short term, short term, medium term and long term load demand, depending on the time horizon. This paper presents an application of neural network for real time short term load forecasting and has been compared with the conventional exponential smoothing technique. The daily load data of an inter connected grid Damodar Valley Corporation, operating under Eastern Regional Load Dispatch Centre, India were used as data sets for training and comparing the performance of different neural network topologies along with conventional exponential smoothing technique. The results obtained from Artificial Neural Networks were evaluated with the statistical parameters i.e., Mean Absolute Percentage Error (MAPE) and Mean Absolute Deviation (MAD). MATLAB has been used for simulation, performance and testing the data. Extensive testing shows that neural network based approach has better forecasting accuracy and robustness.

Keywords: - *Artificial Neural Network (ANN), Cascade Forward Neural Network (CASFNN), Chow's Adaptive Control Method (CACM), Mean Absolute Deviation (MAD), Mean Absolute Percentage Error (MAPE), Radial Basis Function Neural Network (RBFNN), Short Term Load Forecasting (STLF)*

I. INTRODUCTION

In the present complex power system network under deregulated regime, generating companies (GENCOs) must be able to forecast their system load demand and the corresponding price in order to make appropriate market decisions. The economy of power producers, market operators, transmission owners and other players associated with the electricity market is directly affected by the efficiency and the swiftness with which system load is forecasted. An underestimation of load is as severe as an overestimation of load and can bring about humongous losses. Accurate and precise future load estimation is, thus, a prerequisite. In this context, load forecasting emerges as a valuable tool. STLF is required by utility planners and electric system operators for critical operational planning and day-to-day decision making like unit commitment, spinning reserve, economic power interchange, load management etc. Although the time varying system load is influenced by social, metrological and financial factors, their effects are not generally considered in STLF. The success of the important existing STLF methods, such as using statistical techniques or artificial intelligence algorithms, which includes regression models, time series, neural networks, statistical learning algorithms, fuzzy logic or expert systems etc., depends not only on the approach chosen but also on the quality and choice of input data which would contain proper patterns representing the system dynamics. The main motivation for STLF originates from the fact that the loads are much less dependent on each other and the possibility of modeling the slowly varying dynamics of change in load using appropriate STLF techniques. Hence, there are sufficient reasons for continuing further investigations in the field of STLF.

The STLF anticipates very near future loads by analyzing historical data and plays a crucial role in efficient planning, operation, control and maintenance of a power system. Most of the existing techniques on STLF try to improve the performance by selecting different prediction models. But these different models suffer from different problems, like lack of self-learning capability, choice of suitable input, training data etc. Some of the methods are vulnerable to dirty data and rely heavily on the quality and size of historical data. Several techniques have been developed over years to accomplish this challenging task [1-6]. The different methodologies not only differ in the techniques used for forecasting but also in the consideration of factors which influence load. The statistical load forecasting methods include regression method as given in [7], exponential smoothing in [8], time series modeling in [9], Box-Jenkins ARIMA in [10] and others which assume a linear relationship between load and the factors affecting the load. In case of a nonlinearity, such methodologies fail to reflect the appropriate load behavior and thus, are not reliable. Another attempt for load forecast is found in [11] which adopts an expert systems perspective to determine the relationship between historical load patterns and dry bulb temperatures. This system does not employ any specific load model for load prediction. Another similar approach is the development of an adaptive load model in [12] which successfully incorporates the stochastic behavior without utilizing the weather variables. Recently, the genesis of meta-heuristic techniques like Artificial Neural Networks (ANN), Particle Swarm Optimization (PSO), fuzzy logic, Genetic Algorithm (GA) and others have opened up this avenue for further exploration.

The main evolutionary algorithms such as Fuzzy Systems presented in [13] and Pattern Recognition Techniques in [14] have been proposed and used for short term load forecasting applications. Amongst these, artificial neural network is probably the most popular algorithm used for this purpose. The ability of neural networks to easily accommodate complex nonlinear relationships between electrical load and exogenous factors makes them attractive as a tool for load predictions. Besides, neural networks can make accurate predictions without having to select any specific load model [15-18].

This study exploits the capabilities of two different neural network topologies, viz., Cascade Forward backpropagation neural network and Radial Basis Function neural network in making short term load forecasts using historical data for Damodar Valley Corporation (DVC) grid operating under Eastern Regional Load Dispatch Centre (ERLDC), India. The neural networks are trained in the first phase with historical data. The prediction performance of both the neural networks is validated by comparing the predicted data for each day of a week with the actual load demand. Statistical parameters like Mean Absolute Percentage Error (MAPE) and Mean Absolute Deviation (MAD) have been used as performance indices to evaluate the efficacy of the proposed algorithm and to compare the two neural network topologies used with the traditional exponential smoothing method.

The content of this paper is organized in the following manner: Section 2 describes the statement of load forecasting problem and in Sect. 3, an overview of employed methods is offered. Sect. 4 presents the computational procedure of the aforesaid neural networks followed by results and discussions in Sect. 5. Section 6 concludes the work.

II. STATEMENT OF LOAD FORECASTING PROBLEM

Power system load forecasting can be classified in four categories, namely very short-term, short-term, medium term and long term forecasting. The periods for these categories are often not explicitly defined. Different authors use different time horizons to define these categories. STLF covers hourly to weekly forecasts which are often needed for day to day economic operations of GENCOs. Medium-term load forecasting deals with predictions ranging from weeks to a year. Outage scheduling and maintenance of plants and networks are often roofed in these types of forecasts. Long term forecasting on the other hand deals with forecasts longer than a year. It is primarily intended for capacity expansion plans, capital investments, and corporate budgeting. These types of forecasts are often complex in nature due to future uncertainties such as political factors, economic situation, per capita growth etc.

III. AN OVERVIEW OF EMPLOYED METHODS

When forecasts are needed for very large number of items, as is the case in power system load forecasting, smoothing methods are often the only conventional methods fast enough for acceptable implementation as compared to other sophisticated methods. The major advantages of widely used smoothing methods are their simplicity and low cost. The computational time needed for making necessary calculations is less with minimum of outside interference. Due to the above mentioned features, exponential method like Chow's Adaptive Control Method (CACM) has been considered.

III.1 CHOW'S ADAPTIVE CONTROL METHOD (CACM)

Forecasting situations vary widely in their time horizons. Several factors determine actual outcomes, types of load patterns and many other aspects. To deal with such diverse applications, several techniques have been developed. This falls into two major categories: Quantitative and Qualitative methods. Quantitative methods include regression analysis, decomposition method, exponential smoothing and Box-Jenkins methodology.

In this paper, one such exponential smoothing method has been considered. The philosophy is similar to Adaptive-response-rate single exponential smoothing (ARRSES) but has the additional feature that it can be used for non-stationary data. However the way a_t is adjusted in Chow's method is not at all similar to that used in the ARRSES equation.

$$F_{t+1} = \alpha X_t + (1-\alpha)F_t \quad (1)$$

in which α is replaced by α_t,

$$F_{t+1} = \alpha_t X_t + (1-\alpha_t)F_t \quad (2)$$

where

$$\alpha_{t+1} = \left| E_t / M_t \right| \quad (3)$$

$$E_t = \beta e_t + (1-\beta)E_{t-1} \quad (4)$$

$$M_t = \beta\left|e_t\right| + (1-\beta)M_{t-1} \quad (5)$$

$$E_t = X_t - F_t \quad (6)$$

α and β are parameters between 0 and 1 and | | denotes absolute values. Equation (1) indicates that the values of α to be used for forecasting period (t+2) is defined as an absolute value of the ratio of a smoothed error term $(E_t)$and a smoothed absolute error term (M_t). These two smoothed terms are obtained using Single Exponential Smoothing (SES) as shown in equations (3) and (4). Here we could have used $\propto_t$ in equation (1). We prefer $\propto_{t+1}$ because ARRSES is often too responsive to changes, thus using $\propto_{t+1}$ we introduce a small lag of one period, which allows the system to "settle" a little and forecast in a more conservative manner.
Rather, $\propto_t$ is 'adapted' by small increments (usually 0.05) so as to minimize the Mean Square Error. The equations of Chow's adaptive smoothing are

$$S_t = \alpha X_t + (1-\alpha)(S_{t-1}) \quad (7)$$

$$b_t = \alpha_t (S_t - S_{t-1}) + (1-\alpha_t)b_{t-1} \quad (8)$$

and

$$F_{t+1} = S + \left(\frac{1-\alpha_t}{\alpha_t}\right)b_t \quad (9)$$

Artificial neural network has proved its supremacy over traditional methods of load forecasting owing to its capability of learning and self-organizing, robustness in presence of noise, resilience to components failure and tremendous potential for massive computation. ANN can be perceived as multivariate, nonlinear and nonparametric methods. It can easily map a given input-output data pattern and nonlinearity is not a constraint for ANN. But ANN requires optimal network structure and unified training algorithms in order to improve the accuracy of the forecast as well as the performance of the networks. An insightful analysis of neural network structure and underlying operational principles facilitates the design of a better network.

III.2Cascade Forward Backpropagation Neural Network

Cascade forward neural networks are a modified version of the simple feed-forward neural networks. Unlike in feed-forward neural networks, each layer is directly connected to the input. Weighted interconnections exist not only between the input and every layer but each layer is also connected to the successive layers. All the layers have biases. The additional connections amongst the different layers as compared to the feed-forward neural network improve the speed with which the network acquires the desired input-output relationship. Fig. 1 is an illustration of a three layered cascade forward neural network. Evidently, all the layers include a weighted connection with the input. In addition, the first layer is connected to the second layer and the second layer is linked to the third layer as in a feed-forward neural network. An additional connection exists between the first layer and the third layer, thereby imparting an increased learning speed. The weights of interconnection between the previous layers are called input weights while the weights between the layers are referred to as link weights. The hidden layer neurons in this study have been activated by tan-sigmoid transfer function whereas pure linear function has been used for the output layer.

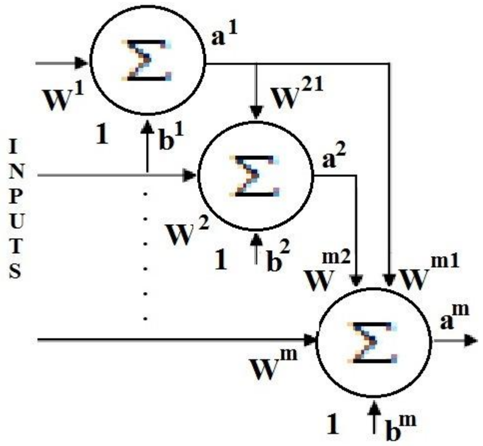

Fig. 1 Architecture of a Cascade Forward Neural Network

where,
p is the input vector.
W^m is the input weight matrix for layer 'm'.
$W^{m,k}$ is the link weight matrix for layer m of layer 'k'.
B^m is the bias of neuron for layer 'm'.
f^m is the activation function used for layer 'm'.
a^m is the output of layer 'm'.

Once the network architecture is defined and the weights and biases of neurons are initialized, neural network training commences. The success of a neural network relies heavily upon the training of the network. The training is usually performed by a supervised algorithm like backpropagation learning algorithm. Backpropagation algorithm is an iterative process and consists of three steps.

i) The first step computes the output of the neural network for the given set of inputs.
ii) The variation between the expected output (target) and the predicted output of neural network is deemed as the error. This error is propagated backwards from the output node to the input node.
iii) Finally, the weights and biases associated with the neurons are adjusted by a multivariate nonlinear numeric optimization algorithm.

A cycle of these steps continues and the weights and biases of neurons are adjusted iteratively in order to minimize error and maximize system performance. Backpropagation is a gradient based approach where the gradient of the performance function given by equation (10) is evaluated to ascertain how the synaptic weights need to be adjusted to achieve the desired goal.

$$E = \frac{1}{2}\sum_p \sum_j (t_{pj} - o_{pj})^2 \qquad (10)$$

where, E is the sum of squared errors, t_{pj} and o_{pj} are the target outputs and actual outputs j for the p^{th} input pattern. In this work, a modified version of backpropagation algorithm called Levenberg-Marquardt Backpropagation is implemented to augment the speed of convergence. The Levenberg-Marquardt algorithm uses equation (11) to constantly adjust network weights and biases.

$$X(n+1) = X(k) - (J^T J + \mu I)^{-1} J^T e \qquad (11)$$

where,
X is the vector of all weights and biases.
J is the Jacobian matrix of the first derivatives of the network errors with respect to weights and biases.
'e' is a vector of network errors and 'μ' is a constant.

III.3 RADIAL BASIS FUNCTION NEURAL NETWORK

Radial Basis Function (RBF) neural network was first introduced in 1988 by Broomhead and Lowe. Radial Basis Function is a special type of function the response of which either decreases or increases monotonically from a central point. RBFNN is usually characterized by the following features:

- They are two-layered feed-forward network.
- A set of radial basis functions is employed by the hidden layers.
- A linear summation function is engaged for the output layers.
- They are much faster during training/learning.
- Network training in RBFs is a two-step process. In the first step, the weights of the input to hidden layers are ascertained. The second step commences with the weight determination of the hidden to output layers.

Various basis functions have been used to model the architecture of RBFNN, such as

- Thin Plate Spine Function: $\phi(x) = x^2 \ln(x)$
- Gaussian Function: $\phi(x) = \exp\left(-\frac{\|x-\mu\|^2}{2\sigma^2}\right)$, where μ and σ are the mean and standard deviation of the distribution respectively.
- Multi-Quadratic Function: $\phi(x) = \sqrt{x^2 + \sigma^2}$
- Linear Function: $\phi(x) = x$

RBF network strives to find the best surface in a multi-dimensional space to ensure the best match to the training data. The general architecture of a RBFNN consists of input layer with as many input nodes as the number of independent input variables, a hidden layer of few neurons employing radial basis transfer function and output layer with as many nodes as the required number of outputs. RBF is prone to overfitting with too many hidden layer neurons and underfitting with too few hidden layer neurons. Fig. 2 exemplifies the architecture of RBF Neural Network. The network distribution density commonly called SPREAD is set at 0.08 in this study.

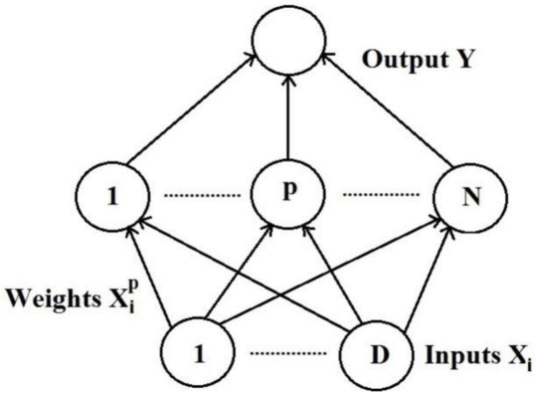

Fig. 2 Architecture of a Radial Basis Function Neural Network

IV. NN BASED PROPOSED METHODOLOGY OF LOAD FORECASTING

In order to accomplish an accurate and useful load forecast, a broad spectrum of associated parameters need to be ascertained.The proposed methodology shown in Fig. 3 for an efficient load forecast is developed in the following discussion in a sequential manner.

IV.1 Selection of Input Data

The input variables in the present model come from historical data corresponding to the factors that affect the load. As inputs the past 96 blocks of each 15 minutes interval for 24 hours of a day are utilized. The proposed NN techniques (CASFNN and RBFNN) were applied for short term load forecast (STLF) in the electricity market forDamodar Valley Corporation (DVC) grid operating under Eastern Regional Load Dispatch Centre (ERLDC), India. DVC Grid consists of an installed capacity of 5000 MW and daily load demand of 3200 MW. The effect of exogenous variables in load variation may be assumed to be taken care of by the neural networks in the classification phase and predicted load demand.

IV.2 Choice of Neural Networks Parameters

Two variations of artificial neural networks in the form of Cascade Forward Neural Network and Radial Basis Function Neural Network are utilized for load forecasting. Different parameters like choice of activation functions for different layers, number of hidden layer neurons and the performance function used for quantifying prediction performance are pertinent for the successful implementation of any neural network. The network details for the different neural networks used in this study are drawn out in TABLE 1. The parameters are selected after rigorous trials for which the network prediction is most accurate. There does not exist any concrete mathematical formulation to facilitate the selection of these parameters.

TABLE1 SELECTION OF PARAMETERS FOR NEURAL NETWORKS

Network Parameters	***CASF NN***	***RBF NN***
Number of Hidden layers	2	2
Activation functions	Tan-sigmoid for hidden layer, Purelin for output layer	Thin Plate Spine Function for hidden layer, Purelin for output layer
Performance Parameters	MAPE, MAD	MAPE, MAD

IV.3DATA PREPROCESSING OR NORMALIZATION

The convergence of neural network output is ensured by normalizing the input data within suitable bounds before training. The neural network has been seen to perform better with normalized inputs than with the original data set, the range of which can be very large. Due to the nature of sigmoid function, the output of the neurons falls within -1 to 1. After rigorous simulations it has been observed that data normalization between 0 to 1 has a superior performance than with normalized data between -1 to 1.Hence, the input data bounds are set to 0 as the lower limit and +1 as the upper limit. Normalization is achieved in accordance with equation (12).

$$Y = (Ymax - Ymin) * \frac{X - Xmin}{Xmax - Xmin} + Ymin \qquad (12)$$

where $X_{min}$is the minimum value of original data set, $X_{max}$is the maximum value of original data set and X is the data point being normalized. Y_{min} and Y_{max} are the minimum and maximum values respectively of the interval boundaries. In this case, Y_{min} = 0 and Y_{max} = 1.

IV.4TRAINING AND VALIDATION

The neural network needs to be trained for faithful prediction of load under varying conditions. The proposed model uses the load patterns for the same days of the previous weeks for its initial training. Once the network has been trained properly, it is made to predict the load demand for the current week. This phase is often called validation. It is an indicator of the accuracy of the predictions.

V. RESULTS AND DISCUSSIONS

In this paper, different topologies of ANN along with conventional smoothing technique were applied to data sampled at 15 minutes interval for different days in a week (seven data sets from 3rd November, 2013-Sunday to 9th November, 2013-Saturday). The forecasting accuracy is ascertained using statistical indices like Mean Absolute Deviation and Mean Absolute Percentage Error. For 'N' number of data points, the following parameters can be defined as follows.

*Mean Absolute Percentage Error (MAPE):*The mean absolute percentage error (MAPE) which is a degree of accuracy in a fitted series value in statistics is expressed mathematically as

$$MAPE = \frac{\sum_{i=1}^{N} |\frac{E_i}{A_i}|}{N} X\ 100\% \qquad (13)$$

where A_i is the actual value, P_i is the predictedvalue and N is the number of data. A MAPE below 5% is the measure of a highly accurate prediction.

Mean Absolute Deviation (MAD): It is one of the robust statistical parameters used to quantify the variability associated with an invariant set of quantitative data. Mathematically, it is expressed as follows.

$$MAD = \frac{\sum_{i=1}^{N} |E_i|}{N} \qquad (14)$$

As described in Section 4, Cascade Forward Neural Network and Radial Basis Function Neural Network are trained using historical data for each day of the previous weeks. For instance, both the neural networks are trained with the load data for two consecutive Mondays of a month. After successful training, the neural networks are made to predict the load demand for the third Monday of the same month using the latest data for the past two Mondays. Effectively, the neural networks make the load forecast for one week in advance. Similar trainings andpredictions are performed for all the days of a week. Such an approach also makes considerations for the fact that load demand is entirely different for the weekends and other days of the week. A neural network trained with the load pattern for a weekday may yield poor results when used for making predictions for a weekend. The approach proposed here counters this deficiency by using load data of previous weekends to predict the load for the current weekend.

The performance of the applied techniques have been compared with more popular smoothing method of STLF namely CACM. The test results are presented in Fig. 4-10.

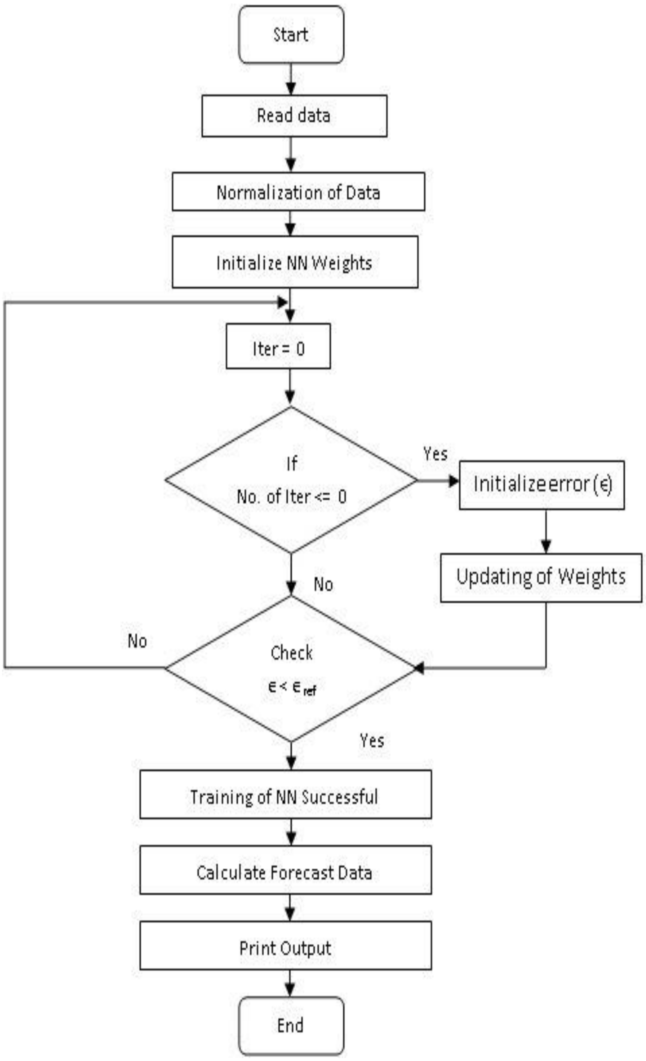

Fig. 3 Simplified flowchart for the proposed methodology

TABLE 2 portrays comparison of MAPE and it is revealed that RBFNN gives comparatively superior predictions and at almost all times predicts the load pattern similar to that of the actual load. The maximum values of MAPE are 0.4652% and 0.8895% for RBFNN and CASFNN respectively in comparison with a maximum MAPE of 0.9199% obtained with CACM. TABLE 3 depicts the comparison of MAD and this again substantiates that RBFNN has a better learning ability than CASFNN and CACM. A maximum MAD in the range of 10.6551 and 14.3792 for RBF NN and CASFNN respectively can be considered to be good and promising for future load prediction applications. From TABLE 4, it has been observed that the proposed application of ANN which does not require any enormous storage size, takes less computational time and memory.

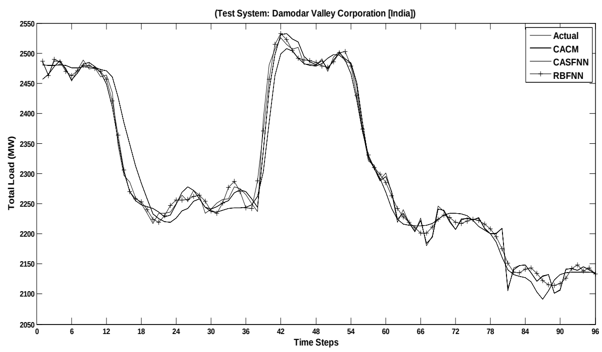

Fig. 4 Comparison of Predicted weekend system loads (Sunday)

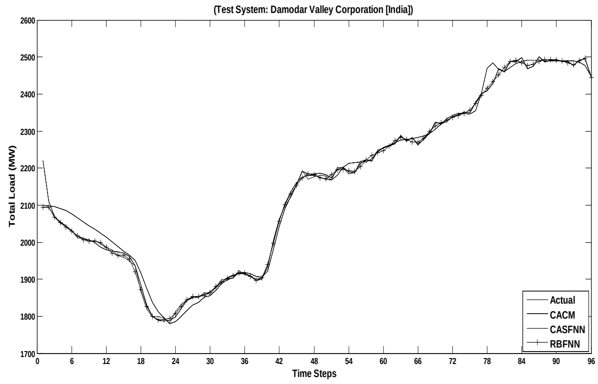

Fig. 5 Comparison of Predicted weekday system loads (Monday)

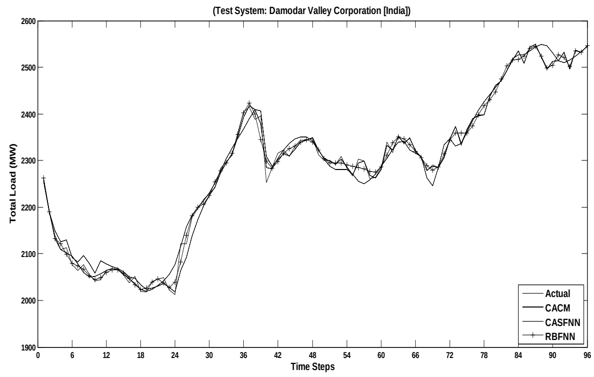

Fig. 6 Comparison of Predicted weekday system loads (Tuesday)

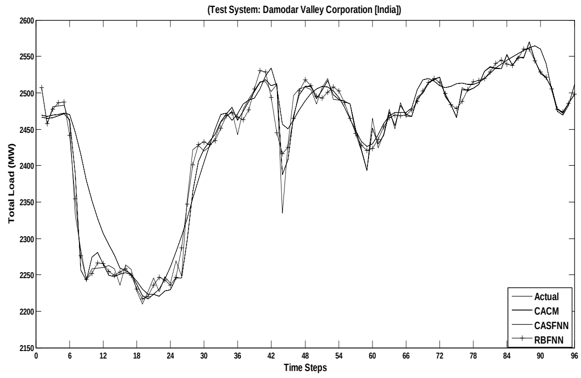

Fig. 7 Comparison of Predicted weekday system loads (Wednesday)

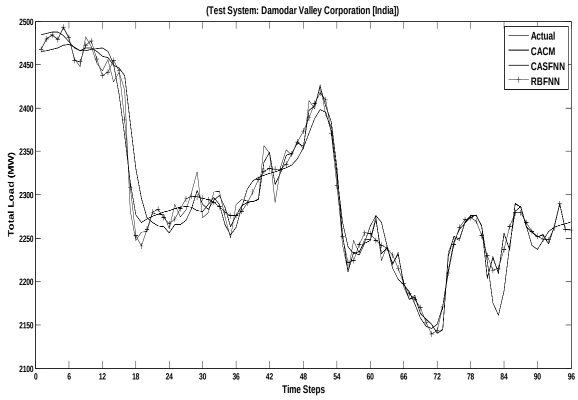

Fig. 8 Comparison of Predicted weekday system loads (Thursday)

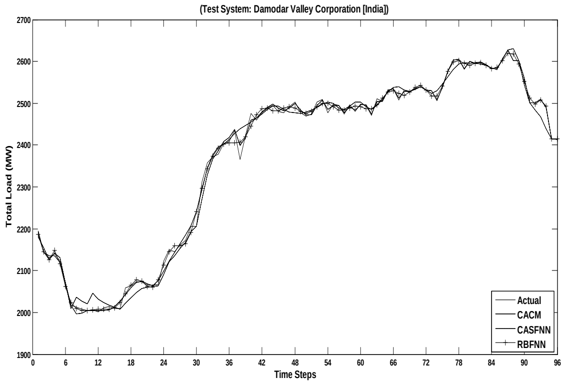

Fig. 9 Comparison of Predicted weekday system loads (Friday)

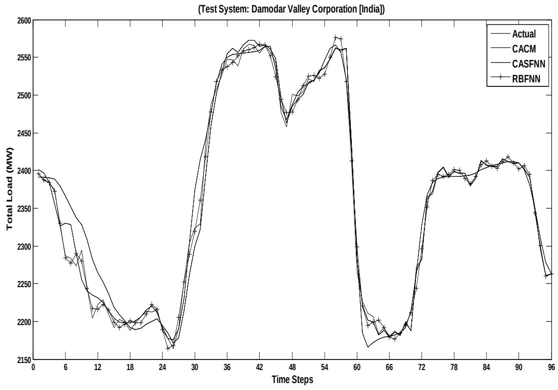

Fig. 10 Comparison of Predicted weekend system loads (Saturday)

TABLE 2 MEAN ABSOLUTE PERCENTAGE ERROR (MAPE) FOR DIFFERENT PREDICTION METHODS

	CACM	*CASFNN*	*RBFNN*
Sunday	0.5159	0.4073	0.4393
Monday	0.9199	0.8895	0.2564
Tuesday	0.7524	0.5529	0.4081
Wednesday	0.6329	0.5697	0.4311
Thursday	0.683	0.6260	0.4652
Friday	0.5910	0.4976	0.3269
Saturday	0.4079	0.3555	0.3599

TABLE 3 MEAN ABSOLUTE DEVIATION (MAD) FOR DIFFERENT PREDICTION METHODS

	CACM	*CASFNN*	*RBFNN*
Sunday	9.7119	9.3146	9.9816
Monday	10.2103	9.3320	5.5069
Tuesday	14.6408	12.5724	9.2883
Wednesday	14.9690	13.8394	10.4300
Thursday	16.5472	14.3792	10.6551
Friday	14.0303	13.6204	7.7507
Saturday	11.7080	8.3055	8.4940

TABLE 4 COMPARISON OF CONVERGENCE TIME (IN SECONDS) FOR DIFFERENT PREDICTION METHODS

	CACM	*CASFNN*	*RBFNN*
Sunday	0.7871	0.4655	0.0375
Monday	0.7795	0.4664	0.0278
Tuesday	0.7982	0.4726	0.0316
Wednesday	0.7799	0.4594	0.0285
Thursday	0.7637	0.4404	0.0279
Friday	0.8561	0.5309	0.0278
Saturday	0.8892	0.4699	0.0284

VI. CONCLUSION

The comparison of the test results shows the merit of Neural Network over the conventional smoothing technique CACM. Simulation test results reveal the following.

The prediction performance of the Neural Networks was very much effective and was able to forecast the load for the next 15 minutes reliably.The forecasting reliability of the proposed ANNs was evaluated by computing the performance indices (MAPE and MAD) and results are very encouraging. On detailed study of the proposed forecast technique, the minimum calculated MAPE of the forecast data is very small.The calculated MAD of the calculated data is very small, which is more reasonable.The application of the proposed ANN has less computational complexity and thus reduced execution time. Hence, proposed methodology is generic enough to be applied to forecasting problems of other power utilities/ load dispatchers for its novelty, simplicity, efficacy and accuracy.

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